Journal of Dry Zone Agriculture, 2018, 4(2): 75 - 83 [©]Faculty of Agriculture, University of Jaffna, Sri Lanka ISSN 2012-8673

Determinants of Herbicide Use in Rice Production Systems of Sri Lanka

Munaweera, T.P. and Jayasinghe, J.A.U.P.

Hector Kobbekaduwa Agrarian Research and Training Institute, Colombo, Sri Lanka

Abstract: This study identifies farm-specific and market factors affecting the adoption of herbicides and the level of herbicide use by rice farmers in Sri Lanka. Determinants of adoption and level of herbicide use were explored using a comprehensive data set collected from 240 randomly selected paddy farmers from selected areas in the Anuradhapura, Ampara, Matara and Kurunegala districts. Study employed the cross sectional Double Hurdle model that describe demand decisions on herbicides arising from two hurdles that have to be overcome for positive demand. Household size, farming experience, type of irrigation, training received related to pest control and extent under cultivation were significant determinants of the decision of farmers to adopt herbicide as an alternative to manual weeding, while, age, sex, extent cultivated, farm gate price, tenurial status, type of irrigation and training related to pest control determine the quantity of herbicide use. Findings highlight the complexity of the issue, hence the institutions seeking to avoid the overuse of herbicide or to encourage adoption of alternative methods of weed control are likely to need to use multiple strategies to address the key variables. The insights generated should be of value to agricultural extension officers, researchers and policy makers. These results are potentially relevant when designing policies to reduce excessive herbicide use or to encourage the adoption of alternative weed control methods such as integrated weed management.

Keywords: adoption, Double-Hurdle model, herbicide, rice

Introduction

Rice cultivation is being challenged by multiple pests and weed considered as the major biotic stress that reducing 30 - 40 percent of rice yield (Abeysekara, 2001). Therefore, proper

and effective weed management techniques are utmost important to acquire better yield from almost all areas of rice producing in Sri Lanka. Traditionally, weed management in rice mainly done through water management

Corresponding author: T.P. Munaweera, e-mail: thilanimunaweera@gmail.com

and manual weeding. However, herbicide application has increased significantly over last decades mainly due to free availability of herbicides in the market at lower prices, water scarcities and labour shortages (Beltran et al, 2013). Weed control using herbicides is the most popular method among farmers nowadays and it allows economically viable weed control providing cost-effective method in the production of agricultural crops. On the other hand, rice cultivation method has shifted from transplanting to direct seeding and herbicide application become a must under this system because under direct seeding difficult to control weed growth by flooding. This has led farmers to apply herbicides indiscriminately creating many negative externalities. Even though the negative externalities associated with pesticides are obvious, farmers use herbicides at increasing trend because marginal increase in pesticide use still appears to be profitable to farmers compared with other alternative weed control methods (Damalas, 2009).

Even though many technical studies have been conducted to find out the chemical properties and pesticide residues in water bodies and food commodities, there are few recent studies on socio-economic aspects of herbicide use in the country. Therefore, this study was designed to analyse the economic and noneconomic determinants of the adoption and level of herbicide use decisions on Sri Lankan rice farms. The investigation of these factors contributes to understanding the factors that motivate the use of herbicides and thus how institutions can further develop appropriate farm programs and projects to promote sustainable agricultural practices while reducing incidence of herbicides misuse. With that background, the objective of this study is to analyse the determinants of the adoption and level of herbicides use decisions on Sri Lankan rice farmers.

Materials and Methods

Cross sectional data for the study were collected from 240 randomly selected rice farmers from selected areas in the Anuradhapura, Ampara, Matara and Kurunegala districts. Above four districts selected based on the total area under paddy cultivation and to represent the three main agro-ecological regions, dry zone, wet zone and intermediate zone. To evaluate the objectives of the study, sample farmers were interviewed personally using a pre-tested structured questionnaire. Among sample farmers, some are using herbicides and some are not using chemical herbicides. In addition, there are differences in level of usage (quantity applied) for unit land area among the users. Literature suggests that farmers' decision to adopt a new technology can be modelled using several theoretical frameworks (Awotide et al, 2014). However, many of the numerous studies that assessed the determinants of farmers' adaptation to new agricultural technology have employed the Logit, Probit or Linear probability models. The Tobit model (Tobin, 1958) was the original and most commonly used model to analyze the functions with zero dependant variable values. However, one of the major drawbacks of the Tobit model is that the decision on whether to adopt or not and how much to adopt are assumed to be made jointly and assume that zero expenditure is attributable to economic factors alone (Newman et al, 2003). Several empirical studies (Blundell and Meghir, 1987; Blaylock and Blisard, 1993; Garcia and Labeaga, 1996; Yen and Jones, 1996) have shown the inadequacy of the standard Tobit model in cross sectional analysis of adoption, connected with its failure in accounting for differences concerning the generation of zero observations. Firstly, the possibility of occurring zero observation due to non-participation in the market for noneconomic reasons were modelled in double hurdle model. In other words, in double hurdle model non-adopters are considered as a corner solution in a utility maximization model (Mal et al., 2012).

Thus, in this paper herbicide usage in rice cultivation was investigated by using Cragg's (1971) Double Hurdle (DH) model by addressing the issues connected to limited dependent variable models. As discussed basic property of this bivariate decision model is that it models the zero value of application of herbicides as a decision result. According to the model, a farmer faces two hurdles while deciding on herbicide application. First hurdle decide whether to use herbicide to control weeds in rice fields. The second hurdle is related to the level of adoption, or what quantity of herbicides to apply. In particular, it postulates that each individual must pass two separate hurdles before they are observed with a positive level of usage. The first hurdle corresponds to factors affecting the decision of using or not using the chemical herbicides and the second to the level of application of the herbicides.

The first hurdle is estimated using Probit model to determine the participation and second hurdle use Tobit model to determine the level of usage (Blundell and Meghir, 1987).

The two decision processes can be formalized as;

The participation decision:

$$d_i^* = \alpha w_i + v_i \tag{1}$$

The consumption decision:

$$y_i^* = \beta x_i + u_i \tag{2}$$

Where d_i^* is the latent discrete variable that represents the pesticide application choice that denotes binary censoring, w_i is the vector of explanatory variables hypothesized to influence pesticide application choice, y_i^* is the latent variable describing the level of pesticide application, x_i vector of variables explaining the quantity of pesticide applied and α and β are vector of parameters to be estimated. v_i and u_i are the standard error term. y_i and d_i are the observed counterparts. Observed variable relate to latent variable such that,

$$d_{i} = \begin{cases} 1, if \ d_{i}^{*} > 0\\ 0, if \ d_{i}^{*} \le 0 \end{cases} and y_{i} = \\ \begin{cases} y_{i}^{*}, if \ y_{i} > and \ d_{i}^{*} > 0\\ 0, if \ otherwise \end{cases} \end{cases}$$
(3)

The dependent variable in the first stage is the farmer's adoption decision (i.e. decision on using or not using pesticides). This variable is binary in nature, taking numeric value 1 for pesticide users, and 0 for non-users. di is the observed quantity of pesticides representing

the respondents' participation decision (i.e. 1 means the respondent is reporting pesticide application greater than 0, and 0 means no chemical pesticide application is reported). The second hurdle involves an outcome equation, which uses truncated model to determine the intensity of pesticide application. This equation uses observations only from farming households who reported positive uses of chemical pesticides. In the second stage, the dependent variable is the amount of pesticide applied. As the variables explaining adoption can also explain the level of adoption (or amount of pesticide applied), the same set of independent variables can be used in both stages. The list of explanatory variables is given in Table 1.

According to Carroll, McCarthy and Carol (2005), equations 1 and 2 are assumed independent, and therefore error terms are randomly and independently distributed as equation 4.

$$\begin{cases} v_i \sim N(0,1) \\ u_i \sim N(0,\sigma^2) \end{cases}$$
 (4)

With the above error term assumptions, the likelihood equation becomes (Burke, 2009; Cragg, 1971)

$$L_{i}$$

$$= [1 - \Phi(\alpha'w_{i})]^{1(d_{i}=0)}$$

$$* \left[\frac{\frac{1}{\sigma_{i}}\varphi\left(\frac{y_{i} - \beta'x_{i}}{\sigma_{i}}\right)\Phi(\alpha'w_{i})}{\Phi\left(\frac{\beta'x_{i}}{\sigma_{i}}\right)} \right]^{1(d_{i}=1)}$$
(5)

If no separate first hurdle exists, everyone is assumed as pesticide users, i.e. $\Phi(\alpha' w_i) =$

 $1\forall_i$ and the model reduced to the Tobit model. Herbicide adoption and demand was analysed separately for two main rice cultivation seasons 2014/2015 *Maha* and 2015 *Yala* season. Factors that determine the adoption of herbicides were analyzed using Tobit model and demand function was analyzed using Probit model using Cragg's Double Hurdle Model approach. General description of the variables used in econometric analysis is presented in table 1.

In adoption model, a discrete latent variable of herbicide use (*adopth*) take a value of 1 if the farmer sprayed with chemical herbicides and 0 if farmer does not use herbicide during the considered cultivation season. In the herbicide use model, latent variable the amount of herbicide active ingredients used per acre of land (*uaih*) used as dependant variable.

Results and Discussion

A positive significant coefficient in the first hurdle Probit model signifies that the corresponding regressor increases the probability of a positive observation in the adoption process. Similarly, in the second hurdle, a positive coefficient means that conditional on a positive of the used amount. Results for the adoption demand models were significant at the 0.01 percent level based on a model Chi square statistics. Significant log-likelihood and LR Chi-square values imply that the model is fitted well and the explanatory variables used in the mode are collectively able to explain the level and determinants of herbicide adoption.

Variable	Description		
Dependant variable			
adopthm	Value 1 if farmers use herbicides in Maha season, 0 otherwise		
adopyhy	Value 1 if farmers use herbicides in Yala season, 0 otherwise		
uaihm	Unit herbicide active ingredients in Maha season		
uaihy	Unit herbicide active ingredients in Yala season		
Independent variable			
Labour and human ca	pital		
age	Age of the farmer (years)		
sex	Value 1 if female, 0 otherwise		
fexp	Number of years in rice farming		
hhsize	Number of total household members		
prempl	Value 1 if full time farmer, 0 otherwise		
training	Value 1 if attended training on pest control, 0 otherwise		
educ	Number of years in school		
Land characteristics			
tstat	Value 1 if farmer owns a farm, 0 otherwise		
extyala	Extent cultivated in Yala season		
extmaha	Extent cultivated in Maha season		
Infrastructure			
irrig	Value 1if irrigated, 0 otherwise		
Type of technology			
seedty	Value 1 if certified seeds, 0 otherwise		
plantigm	Value 1 if transplanting, 0 direct seeding in Maha season		
plantigy	Value 1 if transplanting, 0 direct seeding in Yala season		
Economic variables			
mahaprice	Farm gate price Maha season		
yalaprice	Farm gate price Yala season		
District dummy			
ampara	Value 1 if Ampara district, 0 otherwise		
kurun	Value 1 if Kurunegala district, 0 otherwise		
matara	Value 1 if Matara district, 0 otherwise		

Table 1: Variable description

Estimated results for Double Hurdle model allied to *Maha* season presented in the table 2 and table 3 shows the estimates related to *Yala* season. Family size, farming experience, type of irrigation, training received related to pest control, extent under cultivation were recorded as significant determinants of the farmers' decision in adopting herbicide use, while factors; age, sex, extent cultivated, farm gate price, tenurial status, type of irrigation and training related to pest control determine the quantity of herbicide use.

Household size only significant in adoption model, hence this implies that farmers with larger family size are more likely to adopt herbicides for controlling weeds, but once the farmers decided to use herbicides, their decision regarding the quantity of herbicides to be applied are not affected by household size. Type of irrigation significantly affects adoption and it highlights the importance of water as a determinant of chemical use. Application of herbicides is more effective if water is controlled and positive sign of the coefficient indicate that irrigated farmers apply more chemicals than rainfed farmers. According to the adoption model, results access to formal source of information also affect on the decision of herbicide use. Negative and significant relationship between age and quantity of active ingredient applied indicates that older the farmer lower the level of herbicides applied. Negative and significant relationship of variable sex denotes that female farmers apply lower active ingredients of herbicides than male farmers.

Variable	Adoption (Probit model)		Herbicide a.i.	Herbicide a.i. (Tobit model)	
	Coefficient	S.E.	Coefficient	S.E.	
cons	2.461*	1.302	575.851	300.224	
age	-0.025	0.020	-5.280*	4.053	
sex	-0.289	0.437	-159.268**	85.318	
fexper	0.017	0.019	4.268	3.677	
hhsize	-0.182***	0.074	-21.298*	15.971	
educ	-0.039	0.036	-4.498	7.217	
extmaha	0.119	0.077	16.916*	12.055	
mahaprice			10.309***	3.825	
tstat			-165.771**	85.133	
plantigm			-76.122	115.509	
prempl	0.184	0.366	-40.943	82.098	
seedty	-0.063	0.295	-123.56**	60.944	
training	-0.137	0.290	87.263*	59.903	
irrg	0.571**	0.285	175.405***	60.520	
info	0.828***	0.292	5.559	59.434	
ampara	0.592	0.452	157.213**	83.214	
kurun	-0.101	0.358	-40.825	84.534	
matara	1.209***	0.517	-8.581	97.934	
LR (chi 2)	30.40		54.26		
Log likelihood	-58.566		-1583.689		
Pseudo R2	0.206		0.017		

Table 2: Probit and Tobit paramet	er estimates of he	rbicide use in	Maha Season
-----------------------------------	--------------------	----------------	-------------

***significance at 1%, **significance at 5%, *significance at 10% levels. S.E. = Standard Error

This could be due to female farmers are more likely to use hand weeding than chemical application. Of the land characteristics variables, tenurial status (*tstat*), and cultivated extent significantly affect herbicide quantity. Negative sign of variable tenurial status indicate farmers who own their farm are less likely to use herbicides.

Positive and significant relationship of variable extent under cultivate in demand model implies that with the increase of cultivating land amount of active ingredient applied for unit area is also increasing.

Variable	Adoption (Probit model)		Herbicide a.i. (Tobit model)	
	Coefficient	SE	Coefficient	SE
cons	1.566	1.177	124.882**	343.326
age	-0.013	0.018	-7.572*	4.743
sex	-0.571	0.422	-243.29***	100.541
fexper	0.014	0.016	8.504**	4.312
hhsize	-0.113*	0.065	-3.713	18.595
educ	-0.017	0.031	-9.263	8.448
extyala	0.379***	0.103	26.983**	15.145
yalaprice			14.940***	3.208
tstat	-0.627	0.490	-150.716*	101.166
plantigy			-129.932	133.099
prempl	0.513	0.328	73.311	99.516
seedty	-0.001	0.258	-56.998	72.454
training	0.053	0.252	118.098**	71.210
irrg	0.781***	0.263	247.349***	74.539
info	0.404	0.262	88.356	71.596
ampara	0.183	0.360	233.228***	98.403
kurun	0.173	0.335	187.124**	98.895
matara	1.240***	0.440	288.173***	111.721
LR (chi 2)	58.86		80.92	
Log likelihood	-76.001		-1502.182	
Pseudo R2	0.279		0.026	

Table 3: Probit and Tobit parameter estimates of herbicide use in Yala Season

***significance at 1%, **significance at 5%, *significance at 10% levels. S.E. = Standard Error

Rice farm gate price also positively significant in demand model indicating that with high price farmers are more willing to invest on weed control methods to maximize their net income. Negative and significant values in age and sex variables in demand model suggests that older farmers and women farmers use less herbicides than young and male counterpart. With the increase of years with farming experience farmers tempt to use more quantities of herbicides according to the regression results and this is also ascertain by farmer responses to over using chemicals. Most of the farmers who are applying higher dosage than recommendation give the reason that with their past experience they know recommended dosage is not enough to control weed successfully.

Negative significant relationship of variable *seedty*, which represents the type of seeds used by the farmer suggests that farmers who are using certified seeds apply less herbicide. This implies that if seeds are not coming from certified source it may contain many impurities like weed seeds, hence need more herbicides to control weeds in the field. Participation in pest control related training has positive significant impact on herbicide quantity and this could arise because most of the training events related to pest control in rice cultivation are commonly sponsored and conducted by pesticide companies.

Regional dummy variables for Matara, Kurunegala and Ampara show that region is a key determinant of herbicide use, but its impact is highly variable. These differences could be attributed to specific localized seasonal problems with crop weeds and prevailed climatic conditions etc.

Conclusions

This study examined the factors affecting the adoption and intensity of use of herbicides in Sri Lankan rice-farming systems. Investigation of these factors contributes to improved understanding of the factors that motivate the use of herbicides and factors that determine the quantity applied. Results broadly revealed differences in the key drivers of the adoption and use decisions. Household size, farming experience, type of irrigation, training received related to pest control extent under cultivation are the common variables that have significant effect on the decision on adopting or non-adopting the herbicides in the *Maha* and *Yala* seasons.

According to the Double Hurdle Model analysis, age, sex, extent cultivated, farm gate price, tenurial status, type of irrigation and training related to pest control were identified as common variables having impact on quantity of active ingredients of herbicides applied in both *Yala* and *Maha* seasons.

Finally, the findings of the study highlight the complexity of the issue, with different variables influencing farmer's decisions on whether to adopt herbicides at all, and if so how much herbicides to be used. Institutions intervening to regulate the herbicides use and/ or to encourage farmers to adopt alternative methods in weed control need to use multiple strategies to address the key variables. Further, the results are potentially relevant in designing policies to reduce excessive use of herbicides and to encourage adoption of alternatives.

References

- Abeysekara, A.S.K. 2002. Management of Echinochloa spp. in rice in Sri Lanka. FAO workshop on Echinochloa spp. Control, Beijing, China. 2001; FAO Rice Information, 3:13.
- Awotide, B., Abdoulaye, T., Alene, A., and Manyong, V. M. 2014. Assessing the extent and determinants of adoption of improved cassava varieties in southwestern Nigeria, Journal of Development and Agricultural Economics, 6(9): 376 – 385.
- Beltran, J.C., White, B., Burton, M., Doole, G.J. and Pannell, D.J., 2013. Determinants of herbicide use in rice production in the Philippines, Agricultural Economics, 44(1): 45-55.
- Blaylock, J.R. and Blisard, W.N. 1993. Wine consumption by US men, Applied Economics, 24: 645-651.
- Blundell, R. and Meghir, C. 1987. Bivariate Alternatives to the Univariate Tobit Model, Journal of Econometrics, 34: 179-200.
- Burke, W. J. 2009. Fitting and interpreting Cragg's tobit alternative using Stata, Stata Journal, 9(4): 584.
- Carroll, J., McCarthy, S., and Newman, C. 2005. An econometric analysis of charitable donations in the Republic of Ireland, The Economic and Social Review, 36(3): 229-249.

- Cragg, J. G. 1971. Some statistical models for limited dependent variables with application to the demand for durable goods, Econometrica - Journal of the Econometric Society, 39(5):829-844.
- Damalas, C. A. 2009. Understanding benefits and risk of pesticide use, Scientific Research and Essays, 4:945 - 949.
- Garcia, J. and Labeaga, J.M. 1996. Alternative Approaches to Modelling Zero Expenditure: An Application to Spanish Demand for Tobacco, Oxford Bulletin of Economics and Statistics, 58:489-506.
- Mal, P., Anik, A.R., Bauer, S. and Schmitz, P.M. 2013. Bt cotton adoption: a doublehurdle approach for north Indian farmers, AgBioForum, 15(3):294-302.
- Newman, C., Henchion, M. and Matthews, A. 2003. A double-hurdle model of Irish household expenditure on prepared meals. Applied Economics, 35(9):1053-1061.
- Tobin, J. 1958. Estimation of relationships for limited dependent variables, Econometrica, 26:24-36.
- Yen, S.T. and Jones, A.M. 1996. Individual Cigarette Consumption and Addiction: a Flexible Limited Dependent Variable Approach, Health Economics, 5:105-117.